Analysis and Prediction of Total Retail Sales of Consumer Goods Based on Multiple Regression and SARIMA Model

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Abstract: In order to explore the influencing factors and prediction methods of total retail sales of consumer goods under the new normal of economy, this paper studies the time series data of China from 2007 to 2018, analyzes the influence of multiple economic variables on total retail sales of consumer goods by using multiple regression model, and uses seasonal autoregressive moving average model (SARIMA) to make high-precision fitting. The basis is provided for its short-term prediction, and finally the policy suggestions are given. The results show that the stock of money and quasi money (M2) and the state budget expenditure are positively correlated with the total retail sales of consumer goods; the total retail sales of social consumer goods in China will maintain a rapid growth trend in the future.

1. Introduction

The "Total Retail Sales of Consumer Goods" refers to the amount of non-production and non-business goods which enterprises sell to individuals and social groups through the transaction, as well as providing food and beverage services. It is an important indicator to measure the level of consumption of residents. [1] It is generally believed in the academic circles that the key to increasing the total retail sales of consumer goods is to increase the per capita disposable income of residents.[2-4] The completion of fixed assets investment and financial expenditure also play a leading role in the total retail sales of consumer goods.[5-8] However, almost all of the above studies are based on the analysis of annual data, and the short-term prediction of the total retail sales of consumer goods is not satisfying.[9] Also, it is possible to relax the classical hypothesis test of linear regression in order to provide a higher model fit.

In order to effectively explain the influence factors of total retail sales of social consumer goods increase and forecast it in the short term, we choose a series of monthly economic indicators, using multiple linear regression method to establish a model and verify the classical assumptions, and then apply a SARIMA model to forecast the total retail sales of social consumer goods. In the end, we compare the two kinds of model prediction effect. It is found that money and quasi-money stock (M2) and national fiscal budget expenditure are positively correlated with the total retail sales of consumer goods, of which money and quasi-money stock (M2) have the strongest correlation; retail sales of consumer goods in China will continue to grow rapidly in the future.

2. Sample Description, Model Setting and Variable Description

From the perspective of economic theory and past academic research, influence factors of the total retail sales of social consumer goods (Y) include the money supply, household income, spending, etc. As residents' income for each quarter, its effectiveness in the short term is not significant for the prediction of interpreted variable prediction and policy guidance. So this paper chooses money and quasi money stock (X_1), the national budget expenditure (X_2), the national budget revenues (X_3), fixed asset investment (X_4), the market value of stock circulation (X_5) as explanatory variables, the other influential factors in random perturbation terms. The data used in this paper are all from the national bureau of statistics, China economic database (CEIC) and Tai'an database (CSMAR). In 2007, the fiscal revenue and expenditure subject carried out a big reform, especially the scope of fiscal expenditure item changed a lot, as a result, the previous data cannot be

compared. Therefore, this paper selects the current value of the total retail sales of consumer goods in each month from 2007 to 2018. In order to eliminate the influence of the uncertain factors during the Spring Festival holiday and enhance the comparability of the data, the national bureau of statistics has not released the total retail sales of consumer goods in January and February since 2012, so there are currently $12 \times 10 = 120$ sample data.

Based on the above analysis, the multiple linear regression model is constructed as follows:

$$Y.. = \alpha + ,\beta_{-1}.,X_{-1}.+ ,\beta_{-2}.,X_2 + ,\beta_{3}.,X_{-3} +, \beta_{-4}.,X_4 + ,\beta_{-5}.,X_{-5} + \varepsilon \quad (1)$$

The descriptive statistical results of the data are shown in Table 1.

Table 1 Variable descriptive statistics

name	Variable meaning	Number of observations	Average	Standard Deviation	Minimum	Maximum
Y	Total retail sales of consumer goods	120	19192.937	8355.400	6672.500	35893.500
X_1	M2	120	1025773.699	452430.434	364093.660	1826744.220
X_2	State budget financial expenditure	120	11938.305	6695.532	2874.200	37725.390
X_3	Revenue from the state budget	120	9756.814	3902.299	3144.830	18472.930
X_4	Fixed asset investment	120	36923.492	18196.483	8008.600	81273.000
X_5	Market value of shares outstanding	120	23230.541	13401.735	3770.600	50468.200

3. Empirical Results and Analysis

3.1 Correlation analysis

Firstly, the Pearson correlation test and Spearman correlation test were performed on the data to ensure the effectiveness of the regression model, as shown in Table 2.

It can be seen that the total retail sales of consumer goods are significantly positively correlated with all explanatory variables, indicating that the selection of variables is reasonable. However, there is also a high correlation between explanatory variables, suggesting that multicollinearity may occur.

Table 2 Correlation analysis

Model	Y	X_1	X_2	X_3	X_4	X_5
Y	1	0.991	0.846	0.859	0.949	0.928
X_1	0.985	1	0.829	0.881	0.949	0.934
X_2	0.738	0.711	1	0.661	0.839	0.708
X_3	0.832	0.871	0.536	1	0.878	0.806
X_4	0.926	0.935	0.732	0.871	1	0.903
X_5	0.928	0.935	0.669	0.837	0.883	1

Note: the lower-left part is the Pearson correlation coefficient, and the upper right part is the Spearman correlation coefficient. ** indicates a significant correlation at the 1% level (double-tailed)

3.2 Model regression analysis

Correlation analysis only analyses the interaction between two variables. In order to further explore the influencing factors of the total retail sales of consumer goods, multiple regression analysis is carried out to comprehensively consider the influence of various variables. The regression results after calculation are shown in Table 3.

It is obvious that the model has serious multicollinearity and redundant variables should be deleted. T-test was used to screen the independent variables and check the multiple regression results of the output. The double-tailed significances of X_2, X_4 and X_5 are greater than 0.025, indicating that the test failed.

Table 3 Multiple regression results (1)

	Coefficient	Standard error	t	Significance	Allowance	VIF
(Constant)	1235.940	374.954	3.296	0.001		
X_1	0.017	0.001	16.987	0.000	0.067	14.954
X_2	0.058	0.028	2.069	0.041	0.398	2.511
X_3	-0.251	0.071	-3.536	0.001	0.185	5.418
X_4	0.026	0.021	1.251	0.213	0.096	10.381
X_5	0.043	0.025	1.684	0.095	0.123	8.101
$R^2 = 0.977$			$R^2(adj) = 0.976$			
Standard Error = 1299.954			Durbin-Watson = 1.409			
F = 960.431			P = 0.000[b]			

After deleting X_4 and X_5 successively, the new regression results are obtained in Table 4. The adjusted R^2 is 0.975, indicating that the model constructed in this paper has a high fitting degree. The F value increases significantly after the redundant variables are removed, indicating that the explanatory ability is further enhanced. VIF values are all less than 10, so multicollinearity is at an acceptable level.

The estimated regression equation is:

$$Y. = 1235.94 + 0.017.,X\text{-}_1. + ,0.058X_2 - 0.251X\text{-}_3 \tag{2}$$

If we know the stock of money and quasi-money (M2), the state budget expenditure and the state budget revenue in a given month, we can now estimate or predict the total retail sales of consumer goods in that month. The above mechanism can be understood as that the nominal money circulation enters the social consumption cycle after it is partly precipitated by the state budget fiscal expenditure and the state budget fiscal revenue, which is the so-called state savings.

Table 4 Multiple regression results (2)

	Coefficient	Standard error	t	Significance	Allowance	VIF
(Constant)	849.62	330.769	2.569	0.011		
X_1	0.019	0.001	28.131	0.000	0.156	6.392
X_2	0.074	0.026	2.796	0.006	0.465	2.151
X_3	-0.200	0.065	-3.084	0.003	0.226	4.433
$R^2 = 0.976$			$R^2(adj) = 0.975$			
Standard Error = 1313.684			Durbin-Watson = 1.329			
F = 1565.976			P = 0.000[b]			

3.3 Parameter Test

3.3.1 Overall hypothesis test

Firstly, the overall hypothesis test of the model was conducted to observe whether all regression coefficients were equal to 0 at the significance level of 0.05. The null hypothesis and the alternative hypothesis are

H_0 : $\beta_{-1.} = \beta_{-2,} = \beta_{-3.,} = 0$

H_1 : Not all regression coefficients are equal to 0.

The significance level in the output is 0.000. Since the significance level is less than the preset 0.05, we reject the null hypothesis that these regression coefficients are not all 0.

3.3.2 Single variable hypothesis test

Then we evaluate a single regression coefficient, and use the t-value in the output results to test each regression coefficient. The null hypothesis and the alternative hypothesis are

H_0 : $\beta_{-i.,} = 0$

H_1 : $\beta_{-i.,} \neq 0$

Subscript I represents any independent variables using the same 0.05 significant level. For money and quasi money stock (M2), the state financial budget spending and state budget income, the regression coefficient of p- value is less than 0.01, which shows that the coefficient is not equal to 0, and has significant effect to predict total retail sales of social consumer goods.

3.3.3 Linear regression hypothesis test

Next, we use our regression model to verify the assumption of linear regression. The first assumption is that there is a linear relationship between each independent variable and each dependent variable.

Use y as the vertical axis, X_1, X_2 and X_3 as the horizontal axis to construct the scatter diagram, as shown in Figure 1.
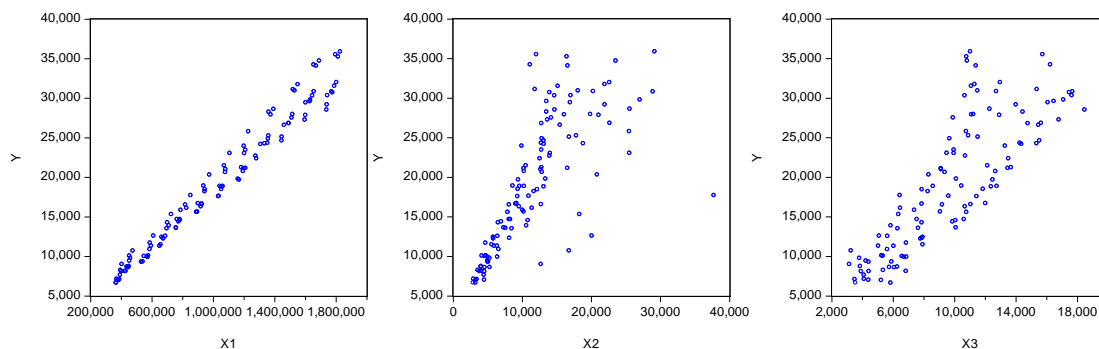

Figure 1 X-Y scatter plot

Total retail sales of social consumer goods for money and quasi money stock (M2) and the state financial budget expenditure presents the overall growth trend. As the increase of money and quasi money stock (M2) or the state budget expenditure, total retail sales of social consumer goods increase at the same time, indicating that the relationship is linear. Obviously, there are no nonlinear characteristics in the data above.

3.4 Test and remedy of heteroscedasticity

3.4.1 Graphic test

Take the square of the regression $RESID^2$ as the ordinate and an explanatory variable X_i in the regression equation as the abscissa, drawing a scatter diagram. If the scatter chart shows a certain trend, the heteroscedasticity can be judged.
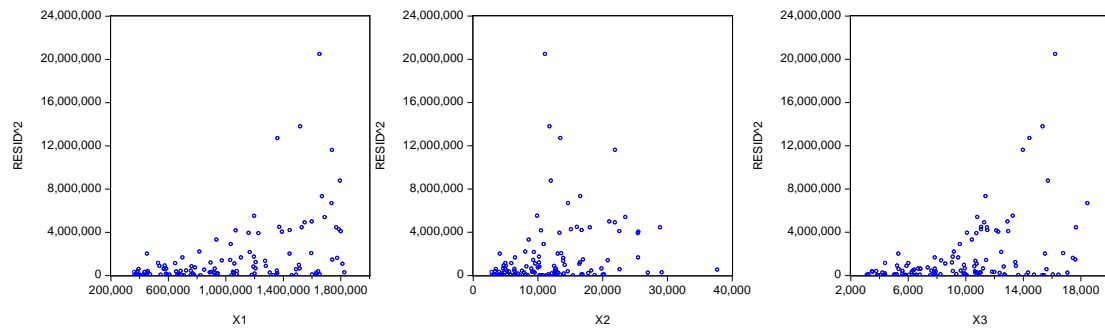
Figure 2 Residual scatter plot

As shown in Figure 2, the residual distribution is flared, suggesting that heteroscedasticity may exist.

3.4.2 White test

White test is provided by H. White in 1980, the heteroscedasticity test of which carried out by constructing an auxiliary regression and using the $\chi 2$ statistic. The null hypothesis and alternative hypothesis tested by White are:

H_0 : , ε has no heteros

H_1 : , ε has heteros

The test results are shown in Table 5. As the sample number is 120, the determination coefficient nR2 of the auxiliary regression function can be calculated as 43.501. Under the null hypothesis, nR^2 asymptotic is subject to the $\chi 2$ distribution with 9 degrees of freedom, and the critical value $\chi_a^2(9)$ is 16.919 when $\alpha=0.05$, which is less than nR^2. The null hypothesis is rejected, indicating that the random error in the model has heteroscedasticity.

Table 5 Outcome of white test

	Coefficient	Standard error	t	Significance
Constant	-443838.6	1540346	-0.288	0.772
X_1^2	-1.03E-05	5.28E-06	-1.961	0.053
$X_1 * X_2$	6.20E-05	0.000	0.188	0.851
$X_1 * X_3$	0.004	0.001	3.702	0.000
X_1	-13.802	7.553	-1.827	0.070
X_2^2	0.005	0.006	0.886	0.377
$X_2 * X_3$	-0.038	0.031	-1.228	0.222
X_2	37.536	227.782	0.165	0.869
X_3^2	-0.259	0.078	-3.316	0.001
X_3	1417.578	691.708	2.049	0.043
$R^2 = 0.363$			$R^2(adj) = 0.310$	
Standard Error = 2533558			Durbin-Watson = 1.962	
F = 6.950			P = 0.000^b	

3.4.3 Weighted least square estimation

When there is heteroskedasticity in the model, it can be proved that the estimator of the ordinary least square method is still linear and unbiased, but it no longer has the minimum variance, that is, the estimator is no longer valid. In this paper, $w_1=1/sqr(X_1*X_3)$ is selected as the weight by using the weighted least squares estimation method to calculate the predicted value of regression standardization and the residual of regression standardization, constructing a new residual diagram.

The result is shown in Table 6.

Table 6 Improved multiple regression results (1)

	Coefficient	Standard error	t	Significance
(Constant)	669.396	182.141	3.675	0.000
X_1	0.018	0.001	29.472	0.000
X_2	0.097	0.018	5.307	0.000
X_3	-0.132	0.059	-2.248	0.027
$R^2 = 0.985$		$R^2(adj) = 0.984$		
Standard Error = 959.333		Durbin-Watson = 1.198		
F = 2479.750		P = 0.000^b		

At this point, the P value of X_3 is greater than 0.025, which cannot meet the requirements of the T-test of a single variable, so the variable is removed. A new regression model is obtained. According to the conclusion of the White test, $w_2=1/X_1$ is used as the weight to re-evaluate the weighted least squares estimation. The analysis result is summarized in Table 7.

Table 7 Improved multiple regression results (2)

	Coefficient	Standard error	t	Significance
(Constant)	523.928	162.896	3.216	0.002
X_1	0.017	0.000	53.662	0.000
X_2	0.111	0.019	5.854	0.000
$R^2 = 0.982$		$R^2(adj) = 0.982$		
Standard Error = 926.248		Durbin-Watson = 0.967		
F = 3249.748		P = 0.000^b		

It can be seen that the value of the F statistic of the re-improved model is increased to 3249.748, indicating that the steps to eliminate heteroscedasticity have successfully optimized the model.

The White test of the model shows that nR^2 was reduced to 5.662, and the critical value $\chi_\alpha^2(2)$ at the significance level of 0.05 was 5.991. nR^2 was less than the critical value, indicating that heteroscedasticity had been removed successfully.

3.5 Verification and remediation of sequence correlation

3.5.1 Durbin-watson test

According to Table 7, the Durbin-Watson test value of the model is 0.967. For the model of the two explanatory variables and the significance level of 5%, we can see from the DW critical value table that, when n=100, dL=1.634, dU=1.715, when n=150, dL=1.706, dU =1.715. As the sample size is 120, the model has a sequence correlation.

3.5.2 Correlation graph and ljung-box Q statistic test

In order to further confirm the existence of sequence correlation in the model, we can use the estimated autocorrelation coefficient and partial autocorrelation coefficient of the regression equation's residual sequence, as well as the Ljung-Box Q statistic to test. The area between the dotted lines is sandwiched by plus or minus twice the estimated standard deviation. If the autocorrelation value is in this range, it can be considered that there is no significant difference from the null hypothesis at the significance level of 5%. In Figure 3, the autocorrelation coefficient and the partial correlation coefficient both exceed the dotted line, so the residual sequence has a sequence correlation.
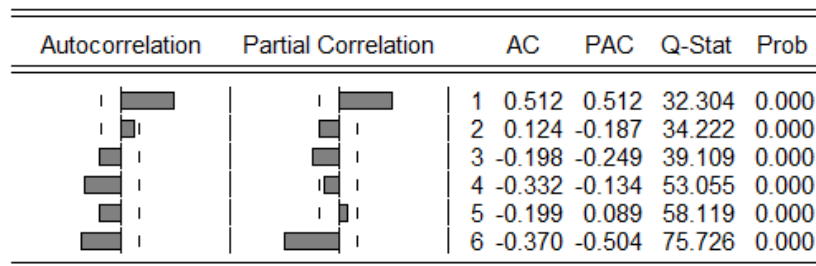
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.512	0.512	32.304	0.000
		2	0.124	-0.187	34.222	0.000
		3	-0.198	-0.249	39.109	0.000
		4	-0.332	-0.134	53.055	0.000
		5	-0.199	0.089	58.119	0.000
		6	-0.370	-0.504	75.726	0.000

Figure 3 Residual sequence correlation diagram

3.5.3 Breush-godfrey LM test

Breush-Godfrey LM test can also be used to test whether there is a higher-order autocorrelation in the residual sequence of the regression equation. The original assumption is that there is no sequence correlation until the p-order lag, as P is a pre-defined integer; the alternative hypothesis is that there is an autocorrelation of order p. Using the LM test, the F statistic was 21.452, the $T \times R^2$ statistic was 32.605, and the p-values were all less than 0.0001, indicating the existence of sequence correlation.

3.5.4 Cochrane-orcutt iterative method

To eliminate sequence correlation, the Cochrane-Orcutt iterative method can be used. According to the results obtained by the Ljung-Box Q statistical test method, we can judge that the residual of the equation has an autocorrelation in order 1, order 3 and order 6 of hysteresis. We modified the model and got the result as shown in Figure 4.

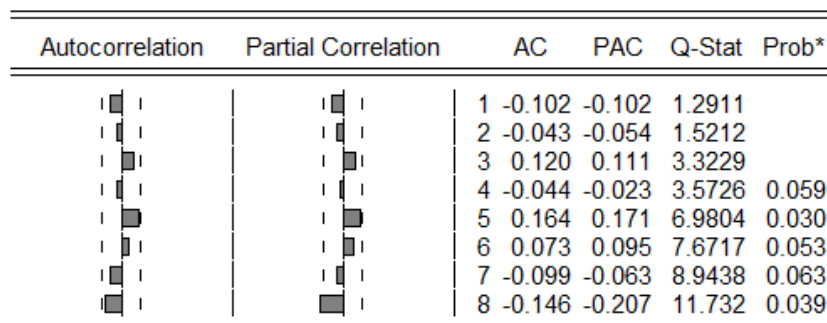| Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.102	-0.102	1.2911	
		2	-0.043	-0.054	1.5212	
		3	0.120	0.111	3.3229	
		4	-0.044	-0.023	3.5726	0.059
		5	0.164	0.171	6.9804	0.030
		6	0.073	0.095	7.6717	0.053
		7	-0.099	-0.063	8.9438	0.063
		8	-0.146	-0.207	11.732	0.039

Figure 4 The modified residual sequence correlation diagram

It can be seen from the above figure that the P values of the Q statistic of each order of hysteresis are above the critical value specified by the 5% significance level, indicating that the residual sequence has no sequence correlation. The final multiple regression analysis result is obtained, which is included in Table 8.

Table 8 The final result of multiple regression

	Coefficient	Standard error	t	Significance
(Constant)	448.047	276.048	1.623	0.107
X1	0.017	0.000	58.916	0.000
X2	0.083	0.016	5.052	0.000
$R^2 = 0.986$		$R^2(\text{adj}) = 0.985$		
Standard Error = 1008.783		Durbin-Watson = 2.195		
F = 1341.780		P = 0.000[b]		

To sum up, the multiple regression equation is
$Y. = 458.047 + 0.017., X\text{-}_1. + ,0.083X_2$

This equation explains 98.6% of the total variation of the total retail sales of consumer goods, and it does not violate the linear assumption of multiple regression, residual normal distribution assumption, non-multicollinearity assumption, homo-variance assumption, and non-autocorrelation assumption.

4. SARIMA Model's Prediction of Total Retail Sales of Consumer Goods

4.1 Application of model

4.1.1 Unit root test for nonstationary sequences

In the field of time series analysis, the ARMA model, ARIMA model and SARIMA model proposed by Box-Jenkins are the commonly used short-term analysis and prediction tools. ARMA(p, q) model is a hybrid model of AR(p) and MA(q), which is only suitable for describing the autocorrelation of a stationary series.[10] If the time series are non-stationary, the stationary sequence should be obtained by difference operation before the model is established.[11]

The ADF test method controls the correlation of higher-order sequences by adding the lagged difference term of the explained variable to the right side of the regression equation:

$$\triangle y_t = \eta y_{t-1} + \sum_{i=1}^{p-1} \beta_i \triangle y_{t-i} + u_t, \quad t = 1, 2, ..., T \tag{3}$$

$$\triangle y_t = \eta y_{t-1} + a + \sum_{i=1}^{p-1} \beta_i \triangle y_{t-i} + u_t, \quad t = 1, 2, ..., T \tag{4}$$

$$\triangle y_t = \eta y_{t-1} + a + \delta t + \sum_{i=1}^{p-1} \beta_i \triangle y_{t-i} + u_t, \quad t = 1, 2, ..., T \tag{5}$$

In the ADF test of total retail sales of consumer goods, the lag period required to eliminate sequence correlation was determined to be 12 according to SIC criterion, and the test results show that its ADF statistic is -2.536876, which is greater than the critical value of three different significance levels (1%, -4.046072; 5%, 3.452358; 10%, -3.151673). Therefore, the time series is non-stationary.

4.1.2 Logarithmic difference transformation

In order to eliminate the heteroscedasticity of time series easily, we first perform logarithmic treatment on the original data ser01 to obtain a new time series ser02 and make a difference at the same time.

The unit root test of time series ser02 shows that the ADF test value of ser02 is -3.848948, which is still greater than the critical value of three different significance levels (1%, -4.048682; 5%, 3.453601; 10%, -3.152400), indicating that the unit root still exists after the first difference.

We perform the difference processing on the time series again and test the time series after the difference by ADF. Finally, the time series d2ser02 is obtained after two differences. The test result shows that ADF=-9.303401, less than the critical value of three different significance levels (1%, -4.046072; 5%, 3.452358; 10%, -3.151673), and the p-value is less than 0.0001. The conclusion that there is no unit root is accepted. Therefore, it can be determined that the sequence of total retail sales of consumer goods is an integer sequence of order 2, which means that the total retail sales of consumer goods of society ~ I(2). By drawing a line graph as shown in Figure 5, it can be seen that the trend of time series has been basically eliminated.
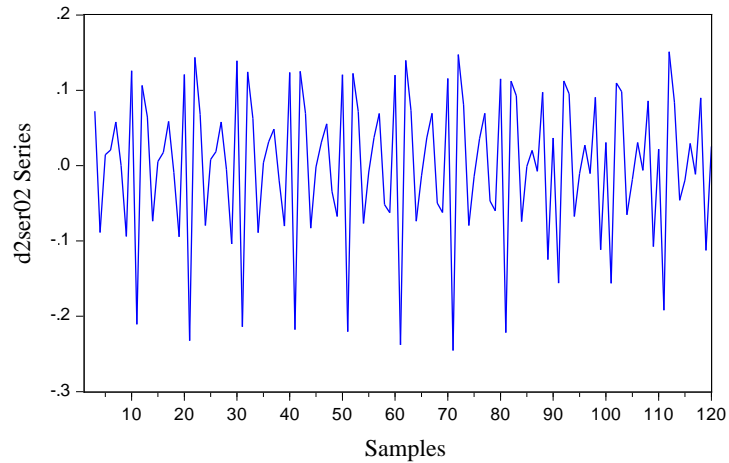
Figure 5 Second-order differential time series line graph

4.1.3 SARIMA model identification

Through two difference operations on ser01 data, we can find from the correlation diagram of time series d2ser02 in Figure 6 that when k=10 or 20, the autocorrelation coefficient will show a relatively large peak, indicating that the sequence contains a certain seasonality, where further seasonal difference is needed. We make a seasonal difference of period S=10 for d2ser02, and the correlation diagram after the difference is shown in Figure 7. The autocorrelation coefficient and partial correlation coefficient of the time series fall into the random region quickly, and the sequence trend is basically eliminated. However, when k=10 or 20, the value is still large, and the seasonality is not completely eliminated. The second seasonal difference is made, and it is found that the seasonality did not continue to improve, so the first-order seasonal difference was finally adopted.

The recognition rule of the time series model is as follows: (1) if the partial autocorrelation coefficient of the stationary time series shows a certain attenuated towing feature, and the autocorrelation function is truncated, it can be judged that it follows a MA(q) process. (2) if the autocorrelation coefficient of the stationary time series shows a certain attenuated towing feature, and the partial autocorrelation coefficient is truncated, it can be judged that it follows an AR(p) process. (3) it is applicable to the ARIMA(p, d, q) model if both autocorrelation function and partial autocorrelation function show a certain attenuation towing feature.[12,13]

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.543	-0.543	35.661	0.000
		2	-0.021	-0.447	35.715	0.000
		3	0.124	-0.240	37.605	0.000
		4	-0.129	-0.304	39.665	0.000
		5	0.133	-0.134	41.887	0.000
		6	-0.115	-0.214	43.570	0.000
		7	0.108	-0.052	45.045	0.000
		8	-0.016	0.034	45.078	0.000
		9	-0.486	-0.888	75.743	0.000
		10	0.891	-0.065	179.92	0.000
		11	-0.487	-0.038	211.31	0.000
		12	-0.022	0.020	211.38	0.000
		13	0.131	0.039	213.69	0.000
		14	-0.137	0.061	216.26	0.000
		15	0.116	-0.080	218.12	0.000
		16	-0.084	-0.047	219.10	0.000
		17	0.088	-0.049	220.18	0.000
		18	-0.012	-0.041	220.20	0.000
		19	-0.434	-0.030	247.10	0.000
		20	0.789	-0.067	337.00	0.000

Figure 6 d2ser02 related diagram

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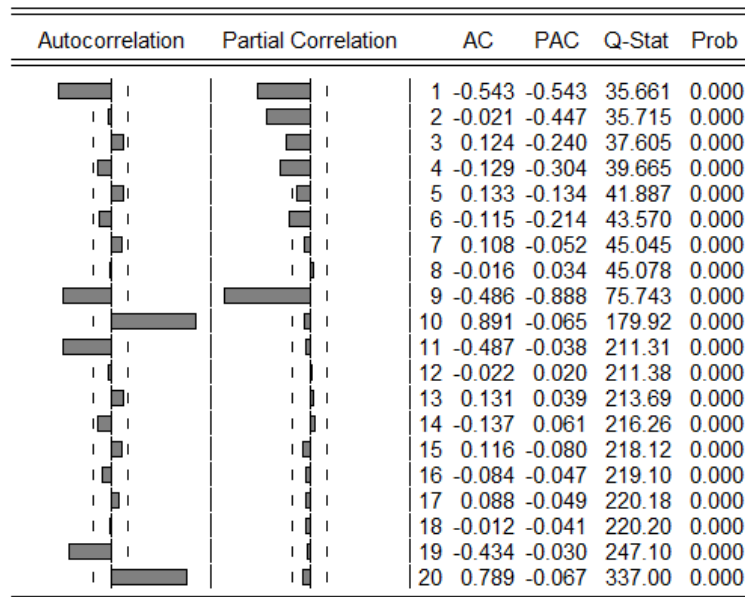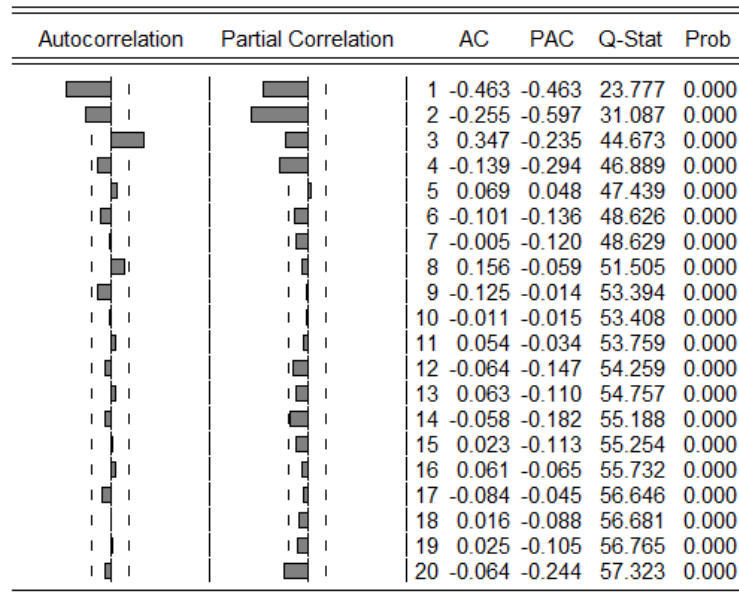| Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.463	-0.463	23.777	0.000
		2	-0.255	-0.597	31.087	0.000
		3	0.347	-0.235	44.673	0.000
		4	-0.139	-0.294	46.889	0.000
		5	0.069	0.048	47.439	0.000
		6	-0.101	-0.136	48.626	0.000
		7	-0.005	-0.120	48.629	0.000
		8	0.156	-0.059	51.505	0.000
		9	-0.125	-0.014	53.394	0.000
		10	-0.011	-0.015	53.408	0.000
		11	0.054	-0.034	53.759	0.000
		12	-0.064	-0.147	54.259	0.000
		13	0.063	-0.110	54.757	0.000
		14	-0.058	-0.182	55.188	0.000
		15	0.023	-0.113	55.254	0.000
		16	0.061	-0.065	55.732	0.000
		17	-0.084	-0.045	56.646	0.000
		18	0.016	-0.088	56.681	0.000
		19	0.025	-0.105	56.765	0.000
		20	-0.064	-0.244	57.323	0.000

Figure 7 Correlation diagram of d2ser02 after seasonal difference

After the above analysis, SARIMA(p, d, q)(P, D, Q)S model is selected to predict the total retail sales of consumer goods, where d and D are the order of difference. From the above judgment, we can know that d=2 and d=1. By observing the correlation graph of sales sequence (the sequence obtained after two difference and one seasonal difference), we can gain p∈{0, 1, 2, 3, 4} and q∈{0, 1, 2, 3} from the distribution of autocorrelation coefficient and partial autocorrelation coefficient. Since there is no large peak of autoregressive coefficient and partial autoregressive coefficient when K=10, we use P={0,1} and Q={0, 1}, but p, q, P and Q cannot be 0 at the same time. For the sake of accuracy, 5×4×2×2-1=79 models are established respectively. In addition, the combinations of p, d, q, P, D, Q that fail t-test and the combinations whose residual is not white noise are removed. After that, there are still 4 combinations left.

4.1.4 Order determination and parameter estimation

The possible models obtained from the above information are SARIMA(3, 2, 0)(0, 1, 0)^S, SARIMA(4, 2, 0)(0, 1, 0)^S, SARIMA(4, 2, 1)(1, 1, 0)^S, SARIMA(4, 2, 1)(0, 1, 1)^S, The results of software inspection are summarized in Table 9.

Table 9 Parameter estimation and test results of different models

The alternative model	AIC	SC	Std
SARIMA(3, 2, 0)(0, 1, 0)^{10}	-5.375	-5.251	0.023
SARIMA(4, 2, 0)(0, 1, 0)^{10}	-5.444	-5.295	0.023
SARIMA(4, 2, 1)(1, 1, 0)^{10}	-5.440	-5.241	0.027
SARIMA(4, 2, 1)(0, 1, 1)^{10}	-5.432	-5.234	0.023

In order to select the model with the best statistical properties, we select the set of orders with the lowest AIC value and SC value as the best order according to the AIC criterion and Schwarz criterion. SARIMA(4, 2, 0)(0, 1, 0)^{10} model are less than those of other SARIMA(p, d, q)(P, D, Q)^S model in the AIC and SC values. Therefore, we choose SARIMA(4, 2, 0)(0, 1, 0)^{10} model.

4.1.5 Diagnostic analysis and testing

Firstly, the residual analysis of the model is carried out. If the time series model is significantly effective, it needs to pass the white noise test, so the values in the residual ACF graph and PACF graph should fall into the random interval.[14] Figure 8 shows that model SARIMA(4, 2, 0)(0, 1, 0)^{10} is a white noise sequence, which can be used for fitting and prediction. The model fitting

diagram is shown in Figure 9.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.005	0.005	0.0033	
		2	-0.037	-0.037	0.1597	
		3	-0.035	-0.034	0.2968	
		4	-0.103	-0.104	1.5008	
		5	-0.076	-0.080	2.1740	0.140
		6	-0.106	-0.118	3.4758	0.176
		7	0.049	0.033	3.7551	0.289
		8	0.016	-0.010	3.7866	0.436
		9	-0.094	-0.119	4.8569	0.434
		10	-0.130	-0.167	6.9197	0.328
		11	-0.094	-0.130	7.9937	0.333
		12	-0.103	-0.158	9.3177	0.316
		13	0.018	-0.047	9.3567	0.405
		14	0.005	-0.096	9.3597	0.498
		15	0.068	-0.047	9.9455	0.535
		16	-0.002	-0.117	9.9459	0.621
		17	-0.052	-0.145	10.305	0.669
		18	-0.020	-0.136	10.359	0.735
		19	0.083	-0.015	11.269	0.733
		20	0.110	0.000	12.914	0.679

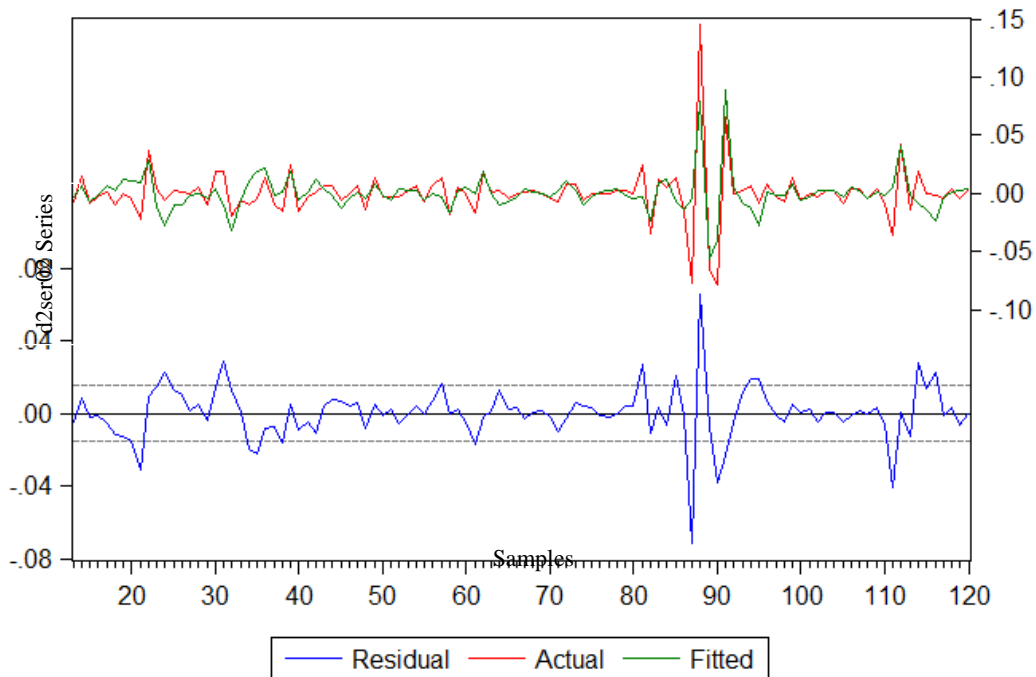Figure 8 SARIMA(4, 2, 0)(0, 1, 0)^{10} Correlation graph of residual sequence

Figure 9 SARIMA(4, 2, 0)(0, 1, 0)^{10} Model fitting diagram

5. Comparison Between Multiple Regression Model and SARIMA Model

SARIMA(4, 2, 0)(0, 1, 0)^{10} model is used to forecast the total retail sales of consumer goods from march to November in 2019. In order to improve the prediction accuracy, this paper adopts the static rolling prediction method, which uses the data from March 2007 to December 2018 firstly to predict the data of March 2019, and then the new time series is used to build a model to predict April 2019, and so on. The prediction effect of the model is shown in Figure 10.
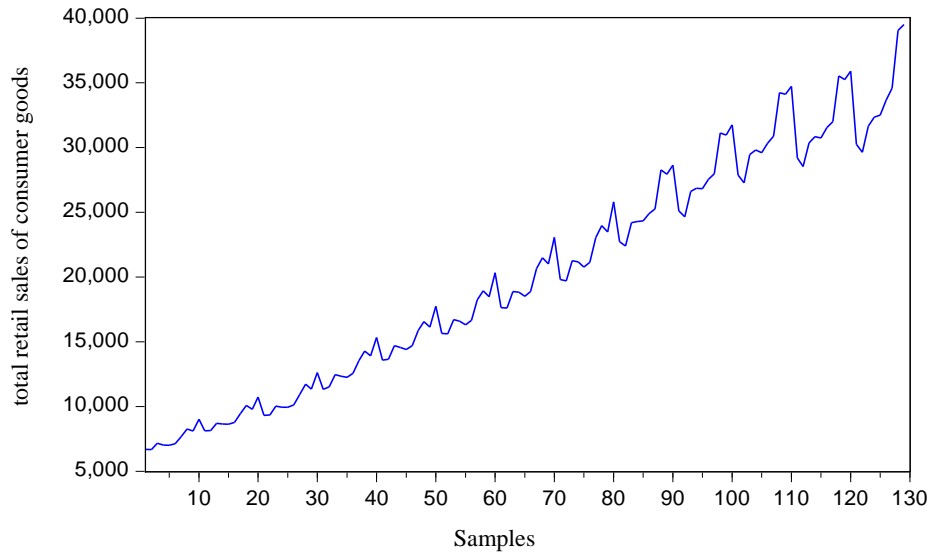
Figure 10 Actual value and forecast value from March 2007 to November 2019

Use the multivariate regression equation $Y = 458.047 + 0.017X_1 + 0.083X_2$ and SARIMA (4, 2, 0)(0, 1, 0)^{10} model on November 3, 2019 social total retail sales of consumer goods to predict respectively, with the result summarized in Table 10.

Table 10 Data model fitting case

Model		Multiple regression model		SARIMA model	
Time in 2019	Actual values	Fitting values	Error	Fitting values	Error
March	31725.70	34679.20	9.31%	30241.51	-4.7%
April	30586.10	33911.60	10.87%	29639.70	-3.09%
May	32955.70	34048.21	3.32%	31639.59	-3.99%
June	33878.10	35653.92	5.24%	32347.76	-4.52%
July	33073.30	34285.31	3.66%	32505.97	-1.72%
August	33896.30	34615.22	2.12%	33666.64	-0.68%
September	34494.90	35766.37	3.69%	34589.45	0.27%
October	38104.30	34527.18	-9.39%	39039.81	2.46%
November	38093.80	35120.06	-7.81%	39492.92	3.67%

The predictive power of the model is generally measured by MAPE (mean absolute percentage error):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\hat{x}_i - x_i}{x_i} \times 100\right| \tag{6}$$

In MAPE formula, $\hat{x}_i$ is the forecast model, x_i is the actual value, and n is forecast periods.

The model has excellent predictive ability when MAPE is less than or equal to 10%. The prediction ability is good at 10%-20% and is reasonable at 20%-50%. Prediction is inaccurate when MAPE is above 50%. According to the above analysis, the MAPE value of the multiple regression model in the period from March to November 2019 is 5.54%, and the MAPE value of SARIMA(4, 2, 0)(0, 1, 0)^{10} model in the same period is 2.51%, both in the "excellent" range.

Based on the above comparative analysis, SARIMA(4, 2, 0)(0, 1, 0)^{10} model is used to forecast the current value of the total retail sales of consumer goods from march to December 2020, and the interval estimations at 95% confidence level have been made. The results are shown in Table 11.

Table 11 Forecast value of total retail sales of consumer goods

Time in 2019	Point estimation	95% lower confidence limit	95% upper confidence limit
March	34344.05	32496.39	36268.83
April	32860.49	30741.17	35086.73
May	35377.55	32775.45	38130.44
June	36665.02	33675.62	39847.65
July	35485.60	32336.81	38857.20
August	36384.38	32915.52	40118.37
September	37031.60	33274.06	41096.30
October	40828.10	36451.09	45584.93
November	40900.25	36294.29	45927.92
December	41632.08	36730.26	47005.11

6. Conclusions and Policy Recommendations

Through the analysis above, we can see that both the multiple regression model and SARIMA(p, d, q)(P, D, Q)^S model can play an important role in the prediction of total retail sales of consumer goods in China. In the short term, SARIMA(p, d, q)(P, D, Q)^S model has a high reliability for the forecast of total retail sales of consumer goods and a small error rate between the predicted value and the real value. The model's error increases over time, so we can use it to provide short-term forecasts and policy guidance.

The results of multiple regression show that the factors that have a greater impact on the total retail sales of consumer goods are money and quasi-money stock (M2) and national budget fiscal expenditure, while the linear relationship between the total retail sales of consumer goods and money and quasi-money stock is the strongest. Regression equation for $Y = 458.047 + 0.017X_1 + 0.083X_2$. With other factors unchanged, for every 100 million yuan increases in M2, total retail sales of social consumer goods increases by an average of 1.7 million yuan. For every 100 million yuan increase in the state budget, the total retail sales of consumer goods will increase by an average of 8.3 million yuan. The results show that under the current circumstances, China's monetary policy is not completely neutral, and the accurate supply of money can enhance China's consumption vitality.

To sum up, based on the coordination and cooperation of the steady monetary policy and active fiscal policy corresponding to the money supply and fiscal expenditure, as well as the continuous promotion of supply-side reform in various fields, the total retail sales of consumer goods in China will continue to maintain a rapid growth trend. As a result, the people's living standards will be further improved.

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